Journal of Cleaner Production 213 (2019) 199–216

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Investigating the factors influencing the uptake of electric vehicles in Beijing, China: Statistical and spatial perspectives

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ARTICLE INFO

Article history:
Received 1 March 2018
Received in revised form
8 November 2018
Accepted 10 December 2018
Available online 15 December 2018

Keywords:
Electric vehicle (EV)
Purchase behaviour
Influential factors
Multinomial logit (MNL) model
Spatial analysis

ABSTRACT

Electrifying urban transportation through the adoption of Electric Vehicles (EVs) has great potential to mitigate two global challenges, namely climate change and energy scarcity, and also to improve local air quality and further benefit human health. This paper was focused on the six typical factors potentially influencing the purchase behaviour of EVs in Beijing, China, namely vehicle price, vehicle usage, social influence, environmental awareness, purchase-related policies and usage-related policies. Specifically, this study used the data collected in a paper-based questionnaire survey in Beijing from September 2015 to March 2016, covering all of the 16 administrative regions, and tried to quantify the relative importance of the six factors, based on their weights (scores) given by participants. Furthermore, Multinomial Logit (MNL) models and Moran's I (a measure of global spatial autocorrelation) were used to analyse the weights of each factor from statistical and spatial perspectives, respectively. The results suggest that 1) vehicle price and usage tend to be more influential among the six factors, accounting for 32.3% and 28.1% of the importance; 2) Apart from the weight of social influence, the weights of the other five factors are closely associated with socio-demographic characteristics, such as individual income and the level of education; 3) people having similar attitudes towards vehicle usage (Moran's I = 0.10) and purchase restriction (Moran's I = 0.14) tend to live close to each other. This paper concludes with a discussion on applying the empirical findings in policy making and modelling of EV purchase behaviour.

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1. Introduction

Electric Vehicle (EV) has been increasingly recognized as a promising alternative to Conventional Vehicle (CV), as promoting the purchase and usage of EVs has great potential to benefit the environment and energy systems at both global and local levels (Zhuge and Shao, 2018a): EVs could reduce the greenhouse gas emissions and improve local air quality (Brady and O'Mahony, 2011; Sovacool and Hirsh, 2009); EVs are more efficient in terms of energy consumption per mile of travel (Åhman, 2001).

This paper uses Beijing, China as a case study, as the Beijing government appears to act actively in electrifying urban transportation, as partly evident from its EV-related policies. These policies can be essentially grouped into purchase and traffic restrictions, which are expected to promote the purchase and usage of EVs, respectively. One typical purchase-related policy for EVs is the license plate lottery policy, which allocates a certain number of purchase permits to CV purchasers at random each year, but provides BEV purchase permits on a first-come-first-serve basis. Therefore, BEV purchasers tend to more easily get permits than CV purchasers (Yang et al., 2014). For example, the winning probability of getting a CV permit was around 0.05% in February 2018. One typical usage-related policy for EVs is the end-number license plate policy: specifically, the usage of CV in Beijing is restricted in a certain area during a specific period (e.g., from 7AM to 8PM) in weekdays, according to the last digit of the license plate. However, this policy does not apply to BEV drivers (Wang et al., 2014).

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https://doi.org/10.1016/j.jclepro.2018.12.099
0959-6526/© 2018 Published by Elsevier Ltd.

In order to increase the adoption of EVs, many empirical studies have been carried out to investigate the influential factors, primarily including socio-demographic attributes, vehicle price, vehicle usage, social influence, environmental awareness and policies (see Section 2.1 for a review). However, little is known about their relative importance. Therefore, this paper attempts to compare the extent to which these key factors may influence the purchase behaviour of EVs at the individual level using the data collected in a questionnaire survey in Beijing. Furthermore, discrete choice models will be used to investigate how the relative importance of each factor may vary across individuals. On the other hand, apart from the so-called "neighbour effects", other spatial characteristics of EV purchase have received relatively scant attention. In response to this, this paper will try to investigate the spatial patterns of the key influential factors, based on the residential locations of the survey respondents.

It should be noted that EV in this paper particularly refers to Plug-in Hybrid Electric Vehicle (PHEV) and Battery Electric Vehicle (BEV), as both of them can be recharged by connecting to the power grid (Zhuge and Shao, 2018a). However, in Beijing, most of the EV-related policies (e.g., end-number licence plate policy and license plate lottery policy) only benefit BEV owners, excluding PHEV ones, as PHEV has a relatively shorter electric driving range and the PHEV drivers may also use petrol on their journeys, which could have negative environmental impact.

2. Literature review

2.1. Factors influencing EV purchase behaviour

EV purchase behaviour could be influenced by various factors, as evident from a large number of empirical studies. In recent comprehensive reviews, different classification methods have been used to group these factor: Li et al. (2017) reviewed the factors influencing the consumers' intentions to adopt BEVs and grouped the factors into socio-demographic, situational and psychological factors; Rezvani et al. (2015) reviewed the drivers and barriers of the uptake of EVs and grouped them into technical factors (e.g., driving range), contextual factors (e.g., charging infrastructures), cost factors (e.g., purchase cost) and individual and social factors (e.g., age and education); Biresselioglu et al. (2018) reviewed the drivers and barriers from "three levels of decision-making, namely formal social units, collective decision-making units, and individual units"; Hardman et al. (2017)'s review was focused on the financial purchase incentives for BEVs. In this paper, a new classification method is proposed for the review of the influential factors, based on the recent reviews above. Specifically, the influential factors here are grouped into socio-demographic attributes, vehicle price, vehicle usage, social network, environmental awareness and policies, which have covered most of the factors reviewed in the recent work, as shown in Table 1.

Next, each of the influential factors above will be reviewed:

2.1.1. Socio-demographic attributes

Socio-demographic attributes, including both individual and household attributes, have been identified as the important factors influencing the adoption of EVs (Li et al., 2017; Rezvani et al., 2015). These socio-demographic factors include age (Hackbarth and Madlener, 2013; Hidrue et al., 2011), gender (Carley et al., 2013; Erdem et al., 2010), education level (Carley et al., 2013; Erdem et al., 2010; Hackbarth and Madlener, 2013; Hidrue et al., 2011), job type (Plötz et al., 2014), income (Erdem et al., 2010; Li et al., 2013a) and number of vehicles (Zhang et al., 2011b).

2.1.2. Vehicle price

Vehicle price is a common factor that could heavily influence the vehicle purchase behaviour. Currently, EV sale price tends to be much higher than CV price, primarily due to the cost of the on-board batteries (Haddadian et al., 2015). Therefore, a number of empirical studies have investigated whether vehicle price could influence the purchase behaviour and if yes, how it could influence (Biresselioglu et al., 2018; Junquera et al., 2016; Larson et al., 2014; Li et al. (2017); Qian and Soopramanien, 2011; Sun et al., 2017; Tamor et al., 2013; Zhang et al., 2011b). In order to reduce the likely negative influence of high sale price of EVs on the adoption, financial incentives (or subsides) have been used in many countries, especially at the early stage of the EV development, including China and the USA (Degirmenci and Breitner, 2017; Fearnley et al., 2015; Jenn et al., 2013; Li et al., 2015; Ozaki and Sevastyanova, 2011; Qian and Soopramanien, 2011; Wang et al., 2017).

2.1.3. Vehicle usage

Vehicle usage here is a broad term used to describe the satisfaction of drivers with their vehicles, considering the operating cost, refuelling/charging time, the availability of charging/refuelling infrastructures, and battery-related concerns (e.g., driving range). Currently, difficult access to charging facilities (e.g., charging posts), long charging time, and limited driving range have been commonly viewed as the barriers to the uptake of EVs, though EV drivers could save energy cost by using electricity. Many EV studies have considered vehicle usage as an influential factor (Biresselioglu et al., 2018; Daziano and Chiew, 2012; Degirmenci and Breitner, 2017; Egbue and Long, 2012; Fearnley et al., 2015; Hackbarth and Madlener, 2013; Hoen and Koetse, 2014; Junquera et al., 2016; Larson et al., 2014; Matthews et al., 2017; Morton et al., 2016; Qian and Soopramanien, 2011; Sun et al., 2017; Tamor et al., 2013; Tanaka et al., 2014; Zhang et al., 2011b). In particular, the battery-related concerns (e.g., driving range), which is one key aspect of vehicle usage, appear to have received more attention (Chéron and Zins, 1997; Clover, 2013; Daziano, 2013; Ewing and Sarigöllü, 1998;

Table 1
Classification Methods used in the Recent Reviews of the Factors Influencing EV Purchase.

Previous Review Work	Socio-demographic Attributes	Vehicle Price	Vehicle Usage	Social Network	Environmental Awareness	Policies
Li et al. (2017)	Socio-demographic factors	Cost	Technical features (e.g., driving range); Experience	Societal influence	Environmental attributes	Government policy
Rezvani et al. (2015)	Individual factors (e.g., age)	Cost	Technical factors (e.g., charging time); Contextual factors (e.g., charging infrastructure)	Social factors (e.g., opinion of peers)	Social factors (e.g., concerns about climate change)	N/A
Biresselioglu et al. (2018)	N/A	Economic restrictions	Lack of charging infrastructure; Technical restrictions	N/A	environmental benefits	Taxes, incentives and regulations
Hardman et al. (2017)	N/A	N/A	N/A	N/A	N/A	Financial purchase incentives

Golob et al., 1993, 1997; Hidrue et al., 2011; Krupa et al., 2014; Lieven et al., 2011; Potoglou and Kanaroglou, 2007; Tamor et al., 2013).

2.1.4. Social network

Social influence is a common factor in the studies of diffusion (e.g., innovation diffusion) (Bakshy et al., 2009, 2012; Li et al., 2013b, 2017; Pettifor et al., 2017; Young, 2009). It is generally argued that individual behaviour, including the purchase behaviour of EVs, could be influenced through the social networks of individuals. For instance, people with a good experience of using EVs may encourage their friends or neighbours to purchase EVs. Essentially, individual behaviour could be influenced by social media and advertisements, their neighbours and friends through the so-called global, neighbour and fiend social networks, respectively. These social influences have also been investigated in the studies of EV adoption (Axsen et al., 2013; Barth et al., 2016; Jansson et al., 2017; Liu et al., 2017; Moons and De Pelsmacker, 2012; Ozaki and Sevastyanova, 2011; Pettifor et al., 2017).

2.1.5. Environmental awareness

As aforementioned, EVs have great potential to benefit the environment: at the local level, EVs do not release vehicular emissions at all when they run on electricity (note that PHEVs can also run on petrol), which could significantly reduce the vehicular emissions and thus improve the local air quality; at the global level, the net reduction in vehicular emissions is closely associated with the fuel type (e.g., coal) used to generate electricity, but EVs allow the management of power production to be centralized to relatively small numbers of power stations, where emission mitigation strategies can be more easily put in place. Therefore, the potential environmental benefits have become one of the important factors influencing the adoption of EVs, as evident from many EV studies (Axsen et al., 2013; Biresselioglu et al., 2018; Daziano and Chiew, 2012; Degirmenci and Breitner, 2017; Delang and Cheng, 2012; Egbue and Long, 2012; Hackbarth and Madlener, 2013; Li et al., 2013a; Ozaki and Sevastyanova, 2011; Smith et al., 2017).

2.1.6. Various policies: purchase and usage-related polices

Apart from the EV subsides mentioned above, there are many other policies being applied in the EV market, and they are expected to promote purchase or/and usage of EVs (Hao et al., 2014). Accordingly, these policies can be essentially grouped into purchase- and usage-related policies: purchase-related policies try to reduce the fixed-cost of EVs; while usage-related policies try to reduce the marginal cost of EVs (Langbroek et al., 2016). Some key EV-related policies are summarized as follows:

- Policies for Vehicle Purchase: subsides, tax incentives (Hackbarth and Madlener, 2013; Langbroek et al., 2016; Li et al., 2015; Mersky et al., 2016; Morton et al., 2016; Zhang et al., 2011b), and license fee exemption (Wang et al., 2017);
- Policies for Vehicle Usage: no driving restriction (e.g., end-number license plate policy) (Sun et al., 2017; Wang et al., 2017), free parking (Hackbarth and Madlener, 2013; Ozaki and Sevastyanova, 2011; Qian and Soopramanien, 2011), priority lane (e.g., bus lane access) (Hackbarth and Madlener, 2013; Mersky et al., 2016; Qian and Soopramanien, 2011), and toll exemptions (Mersky et al., 2016; Ozaki and Sevastyanova, 2011).

Both purchase- and usage-related policies were generally studied within "what-if" scenarios, in order to assess the potential influence of the policies on the uptake and usage of EVs, which could help policy makers to decide whether or not to implement them.

2.2. Methods for the empirical studies of EV purchase behaviour

2.2.1. Data collection methods

Questionnaire survey is a general way to collect the data for the empirical studies of EV purchase behaviour, using one or both of Stated Preference (SP) and Revealed Preference (RP) techniques. They have their own limitations: RP cannot be used to collect data on any objects which do not yet exist (Kroes and Sheldon, 1988); For the SP technique, the stated preferences of respondents may not be real (Wardman, 1988). In the studies of EV purchase behaviour, SP technique (Degirmenci and Breitner, 2017; Delang and Cheng, 2012; Egbue and Long, 2012; Hackbarth and Madlener, 2013; Hoen and Koetse, 2014; Jansson et al., 2017; Junquera et al., 2016; Larson et al., 2014; Li et al., 2013a; Morton et al., 2016; Ozaki and Sevastyanova, 2011; Qian and Soopramanien, 2011; Smith et al., 2017; Sun et al., 2017; Tanaka et al., 2014; Vassileva and Campillo, 2017; Zhang et al., 2011b) tended to be more frequently used than RP technique (Liu et al., 2017; Morton et al., 2016; Tamor et al., 2013). One possible reason may be that most of the countries are still staying at the early stage of transportation electrification, and it is rather difficult to directly survey EV users, due to a relatively low EV adoption rate, though few attempts have been made (Jansson et al., 2017; Larson et al., 2014; Sun et al., 2017; Vassileva and Campillo, 2017).

Questionnaires can either be distributed online or be paper-based. Compared with paper-based questionnaire surveys, online surveys tend to more easily get access to target respondents, but may introduce more bias, as paper-based surveys generally have survey assistants available who can explain about EVs. In the studies of EV purchase behaviour, both online surveys (Egbue and Long, 2012; Hoen and Koetse, 2014; Jansson et al., 2017; Junquera et al., 2016; Li et al., 2013a; Qian and Soopramanien, 2011; Tanaka et al., 2014) and paper-based surveys (Delang and Cheng, 2012; Larson et al., 2014; Ozaki and Sevastyanova, 2011; Sun et al., 2017; Vassileva and Campillo, 2017; Zhang et al., 2011b) have been conducted. In some cases, both of them were used at the same time (Morton et al., 2016; Smith et al., 2017).

2.2.2. Models for the analysis of EV purchase behaviour

Discrete choice models, which can take many forms, have been widely used to analyse the EV purchase behaviour, including mixed logit model (Hackbarth and Madlener, 2013; Hoen and Koetse, 2014), Multinomial Logit (MNL) model (Junquera et al., 2016; Qian and Soopramanien, 2011), nested logit model (Qian and Soopramanien, 2011), hybrid discrete choice model (Smith et al., 2017), generalized discrete choice model (Daziano and Chiew, 2012), binary logit model (Zhang et al., 2011b), conditional logit model (Tanaka et al., 2014) and probit models (Li et al., 2013a). Apart from discrete choice models, some other statistical methods have also been used, including chi-square test (Egbue and Long, 2012) and structural equation modelling (Degirmenci and Breitner, 2017). In addition to statistical analysis of EV purchase behaviour, spatial analysis has also received some attention: For instance, Liu et al. (2017) investigated if the so-called "neighbour effects" could influence the adoption of hybrid EVs, using some general spatial models, including spatial autoregressive, spatial error and geographically weighted regression models. However, the spatial characteristics of EV purchase have not been fully understood yet.

2.3. Comments on previous work

Many empirical studies have been carried out to investigate if a factor could influence the EV adoption, using both statistical and spatial methods. Vehicle price, vehicle usage, social network,

environment awareness, purchase-related policies and usage-related policies appear to be the six key influential factors, which have received substantial attention in the EV studies. However, their relative importance has not been well understood. In response to this, this paper delivered a questionnaire survey in Beijing, China, asking respondents to score these six factors, based on their influence on the EV purchase. Furthermore, socio-demographic attributes, which were identified as influential as well in previous studies, were also collected in the survey and will be further linked to the score (or weight) of each factor, so as to investigate how the relative importance may vary cross individuals. In addition, the spatial characteristics of these six key influential factors, which have received relatively scant attention in the previous EV studies, will also be investigated with a measure of global spatial autocorrelation, Moran's I (Assuncao and Reis, 1999; Waldhör, 1996).

3. Data

As mentioned above, the data used in this paper was collected in a fieldwork in Beijing from September 2015 to March 2016. A paper-based questionnaire survey was carried out in shopping malls to collect the data on vehicle purchase behaviour and social networks. It should be noted that only the data on EV purchase will be used here. The data is composed of two parts: Part 1- Individual Information and Part 2 - Information on Vehicle Purchase. Specifically, Part 2 is used to get the weights of each factor, including vehicle price, vehicle usage, social network (involving in friendship, neighbour and global influences), environmental awareness, purchase restriction and traffic restriction. Participants were asked to score each factor according to their relative importance in terms of influencing EV purchase, given the total score of 100 (see Appendix 1 for more details); Part 1 is used to collect the data on socio-demographic attributes (including both individual and household attributes), which will be related to the weights of each factor using discrete choice models, in order to explore how the relative importance of each factor varies across individuals (see Section 4.2). Furthermore, the residential location of each participant will be geocoded, in order to explore the spatial patterns of the six influential factors (see Section 4.3).

The survey covered all of the 16 administrative regions, namely Dongcheng, Xicheng, Chaoyang, Fengtai, Shijingshan, Haidian, Fangshan, Tongzhou, Shunyi, Chanpin, Daxing, Mentougou, Huairou, Pinggu, Miyun and Yanqing, with 651 samples obtained in total. Note that the target sample size was 550, which was calculated by the formula proposed by Krejcie and Morgan (1970), and the target sample sizes of each administrative region were directly proportional to their population sizes. More details on the sample sizes can be found in Appendix 2 (see Fig. 6 and Table 7). In addition, the distributions of some socio-demographic attributes are shown in Fig. 7 in Appendix 2.

4. Methods

4.1. Clustering analysis: grouping the weights of factors

K-means clustering algorithm, which is a typical clustering analysis method, is used here to organize the weights of each factor into sensible groupings (Jain, 2010), which will be further used as alternatives of the Multinomial Logit (MNL) models to be developed for relating the weights of each factor to socio-demographic attributes (see Section 4.2) and will also be used to explore the spatial patterns of the factors (see Section 4.3). Essentially, the algorithm tries to group the data with the objective of minimizing the sum of the squared error over all K clusters, which is mathematically formulated as Equation (1) (Hamerly and Elkan, 2004; Steinley, 2006).

$$f = \sum_{k=1}^{K} \sum_{x_i \in x_k} \|x_i - \mu_k\| \tag{1}$$

Where, $x_i$denotes one element of a set of points to be clustered; Kdenotes the number of clusters; $\mu_k$denotes the centre point of kth centre; $x_k$denotes the set of points in kth cluster.

In general, the algorithm is composed of four steps below (Hamerly and Elkan, 2004; Steinley, 2006):

Step1: Determine the number of clusters (K) into which the data will be grouped and set the initial centre points of the clusters;
Step 2: Search for the closest cluster centre for each point;
Step 3: Update (or recalculate) the centre point for each cluster;
Step 4: Check if cluster membership stabilizes (for example, the objective values calculated by Equation (1) change slightly over a specific number of consecutive iterations) or the number of iterations exceeds the maximum. If yes, then the algorithm stops; otherwise, it goes back to Step 2.

Determining the number of clusters (K) in Step 1 is critical, but the best K is not often obvious (Hamerly and Elkan, 2004). Some attempts have been made to determine K automatically using different algorithms, including Gaussian-means algorithm (Hamerly and Elkan, 2004), Bayesian model (Kulis and Jordan, 2011), Minimum Description Length (MDL) principle (Bischof et al., 1999) and differential evolution algorithm (Das et al., 2008). This paper will use the same K for all of the factors, in order to compare their differences across individuals in terms of the associated socio-demographic attributes. Specifically, K will be set to 4, meaning that the weight of each factor will be grouped into four clusters. These clusters correspond to four classes, namely "Very High", "High", "Medium" and "Low" according to their central points. For example, the cluster with highest central point will be defined as "Very High", indicating that this cluster contains respondents who gave relatively higher scores to the factor.

4.2. Multinomial Logit (MNL) model: relating the weight of influential factor to socio-demographic attributes

As a typical type of discrete choice model, Multinomial Logit (MNL) model has been widely used to analyse various types of individual behaviour, including the purchase behaviour of EVs (Junquera et al., 2016; Qian and Soopramanien, 2011). This paper attempts to use the MNL models to relate the weight of each factor to socio-demographic attributes (including both individual and household attributes), which are summarized in Table 2. As aforementioned, the weight of each factor will be grouped into four clusters, namely "Very High", "High", "Medium" and "Low", using a K-means clustering algorithm introduced in Section 4.1. The four clusters will be further used as the alternatives of the MNL models for all of the factors, so as to compare their differences in the associated socio-demographic attributes.

A brief introduction to the MNL model is given as follows (Hosmer Jr and Lemeshow, 2004; Long and Freese, 2006; Stata, 2016):

The probability (P_{ni}) for individual$n$ to choose the alternative $i(i = 1, 2, ..., J)$can be calculated with Equation (2). To each factor, alternative $i$in this paper refers to the cluster i, in which the weight of the factor is grouped.

Table 2
Variables used in the MNL models.

Category	Variables	Denotation	Choices
Individual	Sex	Sex	1: Male; 2: Female
	Age	Age	1: ≤18; 2:18–24; 3:25–34; 4:35–44; 5:45–54; 6:55–64; 7: ≥65
	Individual Income	IndIcome	1:≤3K; 2:3–4.5K; 3:4.5–6K; 4:6–8K; 5:8–10K; 6:10–15K; 7:≥15K
	Highest Level of Education	Education	1:Not Educated; 2:Primary-School Level; 3:Middel-School Level; 4:High-School Level; 5:Junior-College Level; 6:Bachelor Degree; 7:Graduate Degree
Household	Number of Driving License	LicenseNum	1:0; 2:1–2; 3:≥3
	Number of Children	ChildrenNum	1:0; 2:1; 3:≥2
	Household Income	HouldIncome	1:≤100K; 2:100–200K; 3:200–300K; 4:300–500K; 5:500–700K; 6:700K-1M; 7:≥1M
	Number of Vehicles	VehicleNum	1:0; 2:1–2; 3:≥3

$$P_{ni} = \frac{e^{u_{ni}}}{\sum_{j=1}^{J} e^{u_{nj}}} = \frac{e^{(V_{ni}+\varepsilon)}}{\sum_{j=1}^{J} e^{(V_{ni}+\varepsilon)}} = \frac{e^{(X\cdot\beta+\varepsilon)}}{\sum_{j=1}^{J} e^{(X\cdot\beta+\varepsilon)}} \quad (2)$$

Where, $u_{ni}$is the utility of alternative i for individual n, which can be further decomposed into the observable (V_{ni}) and unobservable (ε) components. An observable component here is composed of the influential factors (X) and their coefficients (β). In this paper, Xrefers to the socio-demographic attributes in Table 2, and $\beta$is estimated within a statistical software package, Stata (2016). An unobservable component (ε), also known as random term, is generally assumed to follow a specific distribution, such as Gumbel distribution.

4.3. Moran's I: spatial analysis of the factors

In order to further investigate the spatial characteristics of the six factors, Moran's I, a commonly used spatial autocorrelation coefficient (Assuncao and Reis, 1999; Cliff and Ord, 1970; Waldhör, 1996), is computed for the weights (or scores) of each factor, based on the residential locations of the participants, as presented by Equation (3).

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij} \cdot (x_i - \bar{x}) \cdot (x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad (3)$$

where, Ndenotes the number of samples; w_{ij}denotes the Euclidean distance between the residential locations of participants i and j; $x$denotes the weight of a factor; $\bar{x}$is the mean of the weights of a factor. Moran's I usually ranges from −1 to 1. A positive Moran's I (or a positive spatial autocorrelation) suggests that similar values are near to each other; while a negative one suggests dissimilar values are near to each other (Assuncao and Reis, 1999; Cliff and Ord, 1970; Waldhör, 1996).

5. Results

5.1. Weights of the six influential factors

As shown by Fig. 1-(a), vehicle price tends to be the most influential factor among the six factors tested, with a score of 32.3, given the total score of 100; Vehicle usage comes in second, accounting for 28.1% of the importance; Purchase restriction (12.4%), which is a particular purchase-related policy in Beijing, comes third and tends to be more influential than the remaining three factors, namely social network (9.7%), environmental awareness (9.6%) and traffic restriction (7.8%). Further, Fig. 1-(b) shows the weights of the three different social influences, namely friend (5.0%), neighbour (2.0%) and global (2.8%) influences, suggesting that the influence of friends tends to be much more significantly. In addition, the standard deviations of the factors are relatively large, suggesting that the weights of the factors may vary from one participant to another. Therefore, it would be useful to further investigate how individual attributes may influence the weights (see Section 5.2).

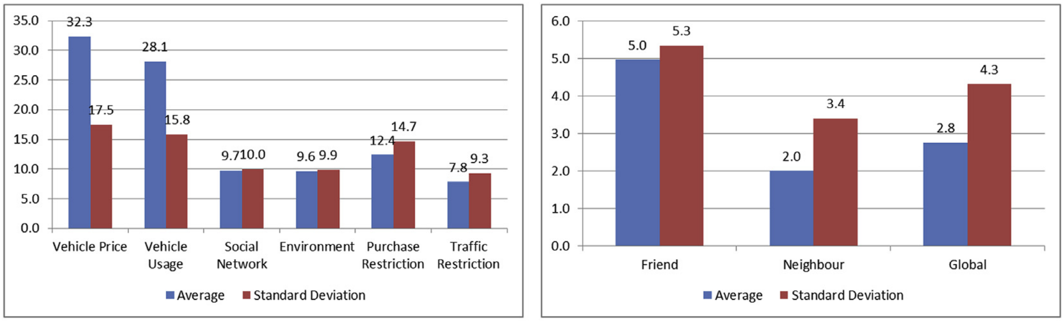
As shown by Table 3 and Table 4, the weights of each factor are grouped into four clusters using the K-means clustering algorithm introduced in Section 4.1. The means in the tables are the centre points of each cluster; the ranges are computed by averaging two adjacent means, as the clustering algorithm searches for the closest centre point for the weights. With the ranges, the distributions of the weights of each factor can be further plotted, as shown in Fig. 2 and Fig. 3. It can be found from the figures that 1) for vehicle price (Fig. 2-(a)), the majority of participants scored above 18, accounting for around 85%; 2) more than half of the participants (55.87%) considered the vehicle usage as 30% of the importance (Fig. 2-(b)); 3) To most of the participants, social influence could be either relatively slight (with a score below 2) or significant (with a score above 8), accounting for 32.79% and 56.98%, respectively, as shown by Fig. 2-(c). Among the three types of social influence (Fig. 3), the neighbour and global influences tend to be slighter (with a score below 1) to the majority of the participants; 4) more than half (58.7%) of the participants viewed environmental factor as the 10% of importance, but around 22% of them paid little attention to the environmental benefits of EVs when they make decisions on vehicle purchase (Fig. 2-(d)); 5) more participants score higher on purchase restriction than traffic restriction by comparing Fig. 2-(e) and -(f), resulting in a higher average weight of purchase restriction from an overall perspective (Fig. 1-(a)).

5.2. Relationships between the weight of influential factors and socio-demographic attributes

Table 5 shows the estimated MNL models for the six influential factors, namely vehicle price (VehPrice), vehicle usage (VehUsage), social network (SocNet), environmental awareness (Environment), purchase restriction (PurchasePo) and traffic restriction (TrafficPo), presenting the relationships between them and socio-demographic attributes (including both individual and household attributes). In general, it is accepted that a variable is statistically significant with the confidence level of 95% if its absolute value of z (|z|) is equal to or greater than 1.96, that is, |z|≥1.96, with the assumption that the data is normally distributed. Next, the statistically significant variables will be identified for each factor according to the z value.

5.2.1. Vehicle price

The statistically significant variables include individual income, the number of children and education level, according the z values (highlighted in bold letters). Based on both the model coefficients and relationships between the weight of vehicle price and these variables (see Fig. 8 in Appendix 3.1), it can be concluded that 1)



(a) Influential Factors (b) Social Influences

Fig. 1. Average weights and standard deviations of the factors.

Table 3
Means and ranges of the influential factors.

Choice ID	Vehicle Price		Vehicle Usage		Social Network		Environmental Awareness		Purchase Restriction		Traffic Restriction	
	Mean	Range	Mean	Range	Mean	Range	Mean	Range	Mean	Range	Mean	Range
1	1.4	<6	0.3	<5	0.0	<2	0.1	<1	0.0	<3	0.1	<3
2	10.9	6–18	9.0	5–15	4.9	2–8	2.7	1–4	5.1	3–9	5.0	3–8
3	26.1	18–39	20.2	15–30	11.3	8–19	5.1	4–10	13.5	9–30	10.4	8–18
4	51.0	>39	39.4	>30	25.8	>19	14.8	>10	45.5	>30	26.3	>18

Table 4
Means and ranges of the three types of social influence.

Choice ID	Friend		Neighbour		Global	
	Mean	Range	Mean	Range	Mean	Range
1	0.05	<1	0.03	<1	0.02	<1
2	2.62	1–4	2.61	1–4	2.79	1–4
3	5.03	4–9	4.99	4–8	5	4–9
4	12.1	>9	10.5	>8	12	>9

people with higher income or more children tend to give relatively lower weights (or scores) to the vehicle price, as these people tend to have higher capacity to purchase; 2) people with higher level of education tend to choose Choice 3 with a score ranging from 18 to 39.

5.2.2. Vehicle usage

The education level is the only statistically significant variable. Roughly, people with higher level of education tend to not choose Choice 1 with a score below 5 (or tend to give a higher score to vehicle usage), as evident from both Fig. 9 in Appendix 3.2 and the model coefficients. One possible reason may be that EV is a typical high-tech product, and thus those well-educated people tend to pay more attention to its usage.

5.2.3. Social network

There appears to be no significant relationships between the weight of social network and socio-demographic attributes. However, the three types of social influence, namely friend, neighbour and global influences are separately associated with several of the attributes, such as individual income and the number of driving licenses, as shown by Table 6. This may be because these three types of social influence differ from each other and could not be simply described with a collective term, social influence (or social network). Therefore, they probably have to be considered separately in the studies of EV purchase behaviour.

5.2.4. Environmental awareness

There are three statistically significant variables in the MNL model for environmental awareness, namely individual income, age and the number of driving licenses. Roughly, the following conclusions could be made according to the model coefficients and relationships shown in Fig. 10 in Appendix 3.3: 1) people with higher individual income tend to not choose Choice 1, meaning that they tend to pay more attention to (or score higher on) environmental awareness; 2) the probability of choosing Choice 3 with a score ranging from 4 to 10 (or scoring higher on environmental awareness) increases, as people get more driving licenses. This may be because people's environmental awareness become stronger, as more and more their household members use vehicles for their daily travel.

5.2.5. Purchase restriction

The education level is found as the only statistically significant factor influencing people's attitudes towards purchase restriction. Roughly, people with higher level of education tend to not choose Choice 1 (or to pay higher attention to purchase restriction), as evident from Fig. 11 in Appendix 3.4.

5.2.6. Traffic restriction

The number of vehicles owned is identified as the only statistically significant variable to the weight of traffic restriction. Specifically, people with more vehicles tend to not choose Choices 2 or 3 with a score ranging from 3 to 18 (Fig. 12 in Appendix 3.5). In other words, these people tend to pay either higher or lower attention to traffic restriction. The reasons may be that on one hand, people with more vehicles may care more about traffic restriction, and thus give higher scores; On the other hand, these people could use different vehicles for their daily travel and tend to more easily get rid of traffic restrictions, and thus may give lower scores. For example, in response to the end-number license plate policy, people with more vehicles could use different vehicles in weekdays according to the license plate numbers. As a result, traffic restrictions tend to be less influential to them.

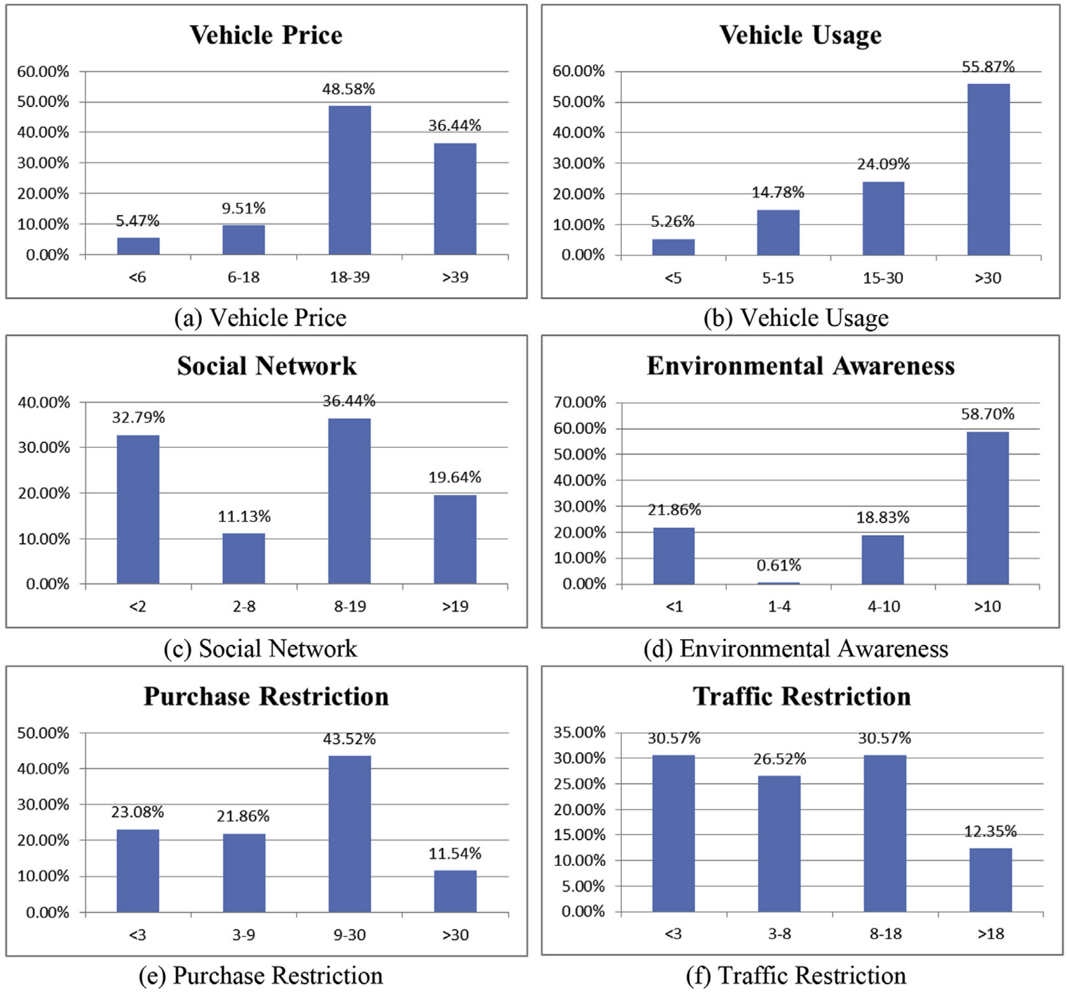


Fig. 2. Distributions of the weights of the six factors.

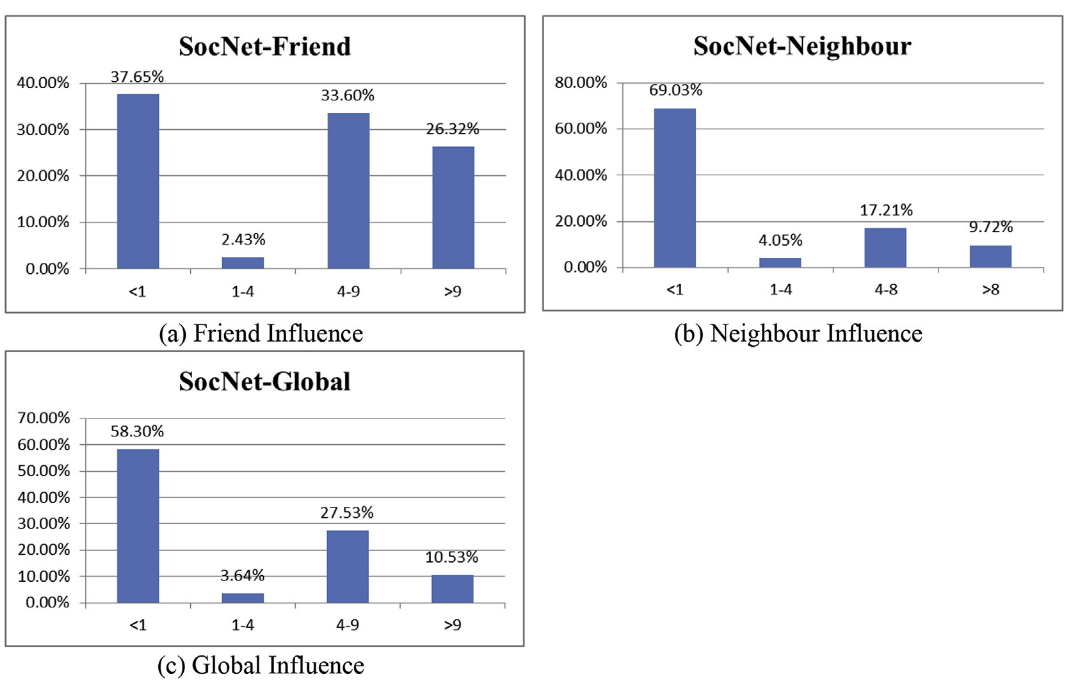


Fig. 3. Distributions of the weights of the three types of social influence.

Table 5
MNL models for the influential factors.

Variable	VehPrice		VehUsage		SocNet		Environment		PurchasePo		TrafficPo	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Choice 1	**Chocie 1: <6**		**Chocie 1: <5**		**Chocie 1: <2**		**Chocie 1: <1**		**Chocie 1: <3**		**Chocie 1: <3**	
Sex					−0.07	−0.26	−0.40	−1.68				
Age					−0.12	−0.82	0.21	1.65				
Indincome	0.35	**2.87**			0.15	1.67	−0.15	**−2.16**				
Education	0.05	0.24	−0.37	**−2.42**	−0.07	−0.58			−0.45	**−2.68**		
MemberNum					0.18	0.57						
ChildrenNum	0.67	1.9			−0.25	−0.96						
LicenseNum					−0.25	−0.90	0.07	0.32			0.16	0.51
HouIncome					−0.09	−0.64						
VehicleNum					0.14	0.47					−0.58	−1.77
Constant	−4.33	−3.33	−0.34	−0.42	1.45	1.31	−0.659996	−0.97	3.25	3.27	1.54	2.41
Choice 2	**Chocie 2: 6-18**		**Chocie 2: 5-15**		**Chocie 2: 2-8**		**Chocie 2: 1-4**		**Chocie 2: 3-9**		**Chocie 2: 3-8**	
Sex					0.11	0.31	−0.76	−0.6				
Age					−0.06	−0.30	0.88	**2.18**				
Indincome	0.28	**2.84**			0.09	0.70	−0.53	−1.41				
Education	0.12	0.77	0.07	0.54	0.06	0.34			−0.27	−1.58		
MemberNum					−0.33	−0.75						
ChildrenNum	0.70	**2.43**			0.04	0.10						
LicenseNum					0.21	0.57	0.18	0.2			0.27	0.85
HouIncome					−0.14	−0.76						
VehicleNum					0.26	0.69					−0.71	**−2.11**
Constant	−3.95	−3.71	−1.69	−2.38	−1.39	−0.89	−5.21	−1.56	2.21	2.16	1.41	2.16
Choice 3	**Chocie 3: 18-39**		**Chocie 2: 15-30**		**Chocie 3: 8-19**		**Chocie 3: 4-10**		**Chocie 3: 9-30**		**Chocie 3: 8-18**	
Sex					0.01	0.03	0.21	0.85				
Age					−0.17	−1.11	−0.11	−0.71				
Indincome	0.09	1.53			0.09	1.00	0.07	0.93				
Education	0.24	**2.45**	0.06	0.6	0.20	1.50			−0.35	**−2.21**		
MemberNum					0.28	0.90						
ChildrenNum	0.23	1.17			−0.25	−0.98						
LicenseNum					−0.34	−1.24	0.65	**2.91**			0.36	1.17
HouIncome					−0.05	−0.38						
VehicleNum					−0.01	−0.04					−0.75	**−2.28**
Constant	−1.63	−2.52	−1.19	−2	0.47	0.42	−2.70	−3.5	3.35	3.52	1.42	2.22
Base = Choice4	**Choice4: > 39**		**Choice4: > 30**		**Choice4: > 19**		**Choice4: > 10**		**Choice4: > 30**		**Choice4: > 18**	

The findings above suggest that individual income and education level tend to be more statistically significant than other socio-demographic attributes, and are associated with four of the influential factors, namely vehicle price, vehicle usage, environment, and traffic restriction. This may be because income and education level are closely associated with affordability and environmental awareness, respectively, which could influence the adoption of EV, as EV generally has a high sale price, but could potentially benefit the environment. Based on the separate analyses of each factor above, the differences between the factors in the associated socio-demographic attributes could be further investigated as follows: 1) people with higher education level tend to give lower scores (or choose Choice 1) to both vehicle usage and purchase restrictions; 2) people with higher individual income tend to pay less attention to vehicle price (or choose Choice 1), but have higher environmental awareness (or not choose Choice 1).

5.3. Spatial patterns of the factors influencing the uptake of EVs

Fig. 4 shows the spatial distributions of the weights of the six factors and Fig. 5 is focused on the three types of social influence, namely friend, neighbour and global influences. Each dot in the maps represents the residential location of a participant. For each factor, the weights are grouped into four clusters, using the K-means clustering analysis (see Tables 3 and 4). Furthermore, Moran's I (see Section 4.3) is computed for each factor, in order to judge whether any spatial patterns could be discerned. As aforementioned, the survey tried to cover all of the 16 administrative regions, and the targeted sample size of each region was proportional to the population size of the region (see Table 7 and Fig. 6 in Appendix 3). As a result, the participants tended to be those who live in the central districts and the central areas of the outer districts, as the population density of these areas tended to be higher. Therefore, the dots (or the residential locations) in the maps tend to be dense in these areas.

It can be found from the maps that 1) people with similar attitudes towards vehicle usage (Moran's I = 0.10) and purchase restriction (Moran's I = 0.14) tend to live close to each other. This may be because the education level is identified as the only statistically significant variable for both vehicle usage and purchase restriction, according to their MNL models (see Table 5), and people with the same level of education (Moran's I = 0.29) tend to live close to each other; 2) the Moran's I of environmental awareness is −0.07, suggesting that people scored differently on environmental awareness a bit tend to live close to each other; 3) there appears to be no significant spatial patterns for the factors of vehicle price (Moran's I = −0.004), social network (Moran's I = −0.01) or traffic restriction (Moran's I = 0.04). For the social influences, people with the similar attitudes towards the neighbour influence (Moran's I = 0.07) a bit tend to live close to each other; while there seems no significant spatial patterns for friend influence (Moran's I = −0.01) or global influence (Moran's I = −0.01).

Table 6
MNL models for the three types of social influence.

Variable	Friend		Neighbour		Global	
	Coef.	z	Coef.	z	Coef.	z
Choice 1	**Chocie 1: <1**		**Chocie 1: <1**		**Chocie 1: <1**	
Age					−0.35	**−2.38**
Indincome	0.11	1.57				
Education	−0.22	**−2.02**				
MemberNum	−0.29	−1.22				
LicenseNum			−0.30	−0.97	−0.52	−1.70
HouIncome			0.13	0.85	0.15	0.99
VehicleNum			−0.03	−0.09	0.40	1.20
Constant	1.57	2.17	2.31	3.52	2.86	3.75
Choice 2	**Chocie 2: 1-4**		**Chocie 2: 1-4**		**Chocie 2: 1-4**	
Age					−0.42	−1.37
Indincome	0.38	**2.18**				
Education	0.06	0.19				
MemberNum	−0.33	−0.48				
LicenseNum			−1.17	**−2.12**	−1.30	**−2.3**
HouIncome			0.32	1.38	−0.04	−0.14
VehicleNum			0.67	1.15	0.93	1.55
Constant	−3.782562	−1.71	−0.45	−0.41	1.31	0.97
Choice 3	**Chocie 3: 4-9**		**Chocie 3: 4-8**		**Chocie 3: 4-9**	
Age					−0.4634608	**−2.74**
Indincome	0.03	0.39				
Education	0.07	0.58				
MemberNum	−0.41	−1.63				
LicenseNum			−0.52	−1.41	−0.63	−1.87
HouIncome			0.24	1.39	0.35	**2.21**
VehicleNum			−0.13	−0.33	0.22	0.61
Constant	0.29	0.37	1.25	1.65	2.44	2.93
Base = Choice4	**Choice4: > 9**		**Choice4: > 8**		**Choice4: > 9**	

6. Discussion on applying the empirical findings

The empirical findings above could be further used for EV-related policy making and modelling of EV purchase behaviour. Two specific examples are given as follows:

6.1. Application in policy making

As aforementioned, vehicle price and usage tend to be more important than the other four factors, accounting for 32.3% and 28.1% of the importance, respectively. Therefore, the EV-related policy makers are suggested to pay more attention to these two factors when shaping policies. In response to the relatively high EV sale price, financial incentives (e.g., EV subsides) should be effective strategies, which could significantly promote the purchase and usage of EVs. For vehicle usage (which is a broad term here involving in charging time, the availability of charging facilities and driving range), it would be very helpful to invest in charging infrastructures, including both slow charging posts at parking lots and fast enroute charging stations (e.g., battery swap stations), so as to increase the degree of people's satisfaction with the use of EVs and then to promote the uptake of EVs.

6.2. Application in modelling of EV purchase behaviour

The approaches to modelling the purchase behaviour of EVs primarily include discrete choice models (He et al., 2014; Lee et al., 2012; Nemry and Brons, 2010), agent-based models (Brown, 2013; Cui et al., 2012; Eppstein et al., 2011; McCoy and Lyons, 2014; Mueller and de Haan, 2009; Pellon et al., 2010; Shafiei et al., 2012; Tran, 2012) and system dynamics (Linder, 2011; Shepherd et al., 2012; Struben and Sterman, 2008). The former two models investigate the purchase behaviour at the individual level; while the latter predicts the EV penetration rates at the system-level (or macro-level). The empirical findings of this paper are presented at the individual level and thus tend to be more straightforwardly used for the former two model types: specifically, the empirical findings can be used to develop a utility function for both discrete choice models and agent-based models to simulate how individuals choose among different vehicle types (Kieckhafer et al., 2009; Mueller and de Haan, 2009; Zhang et al., 2011a), including CVs and EVs, as presented by Equation (4). The theoretical basis of the function is as follows:

- Utility maximization theory has been widely used to model the purchase behaviour of EVs, with the assumption that individuals always try to maximize their own utilities when choosing vehicles, using the influential factors as model variables (Kieckhafer et al., 2009; Mueller and de Haan, 2009; Zhang et al., 2011a). Similarity, the utility function (U) in this paper also incorporates the influential factors (V_i) above, namely vehicle price, vehicle usage, friend influence, neighbour influence, global influence, environmental awareness, purchase restriction and traffic restriction. It is worth noting that the three types of social influence are used here instead of the factor of social network, as it is found that the collective term of social network is not directly associated with any individual attributes (as discussed in Section 5.2).
- The extent to which each factor influences the decision-making on vehicle purchase is mathematically formulated as the weight of each factor (W_i), which varies from one individual to another, according to the findings in Section 5.2. Therefore, the MNL models, which relate the weight of each factor to socio-demographic attributes (see Section 5.2), can be used here to estimate the weight for each individual, so as to take into account heterogeneity. When heterogeneity in not necessarily considered, the average weight of each factor (see Fig. 1) could be used instead of the MNL models.
- The utility function also incorporates a random term (ε), which is used to describe the influence of those unobserved factors. In general,ε is assumed to follow a Gumbel distribution (Cascetta and Papola, 2001; Conniffe, 2007; Zhuge and Shao, 2018b; Zhuge et al., 2016b).

$$U = \sum_i^I U_i + \varepsilon = \sum_i^I W_i \cdot V_i + \varepsilon \tag{4}$$

Where, U_i denotes the utility of ith influential factor (e.g., vehicle price and vehicle usage), which is the product of the weight (W_i) and the observed value (V_i) of the factor.

7. Conclusions

This paper used the capital of China, Beijing as a case study and explored the relative importance of the six typical factors, which could heavily influence the purchase behaviour of Electric Vehicles (EVs), using the data collected from a paper-based questionnaire survey from September 2015 to March 2016. The overall weights (or scores) of the six factors, namely vehicle price, vehicle usage, social network, environmental awareness, purchase restriction and traffic restriction were 32.3%, 28.1%, 9.7%, 9.6%, 12.4% and 7.8%, respectively, suggesting that people cared more about vehicle price and usage than the other four factors. Then, several Multinomial Logit (MNL) models were developed to relate the weights of each factor to socio-demographic attributes, including both individual and household attributes. The results indicate that people's attitudes

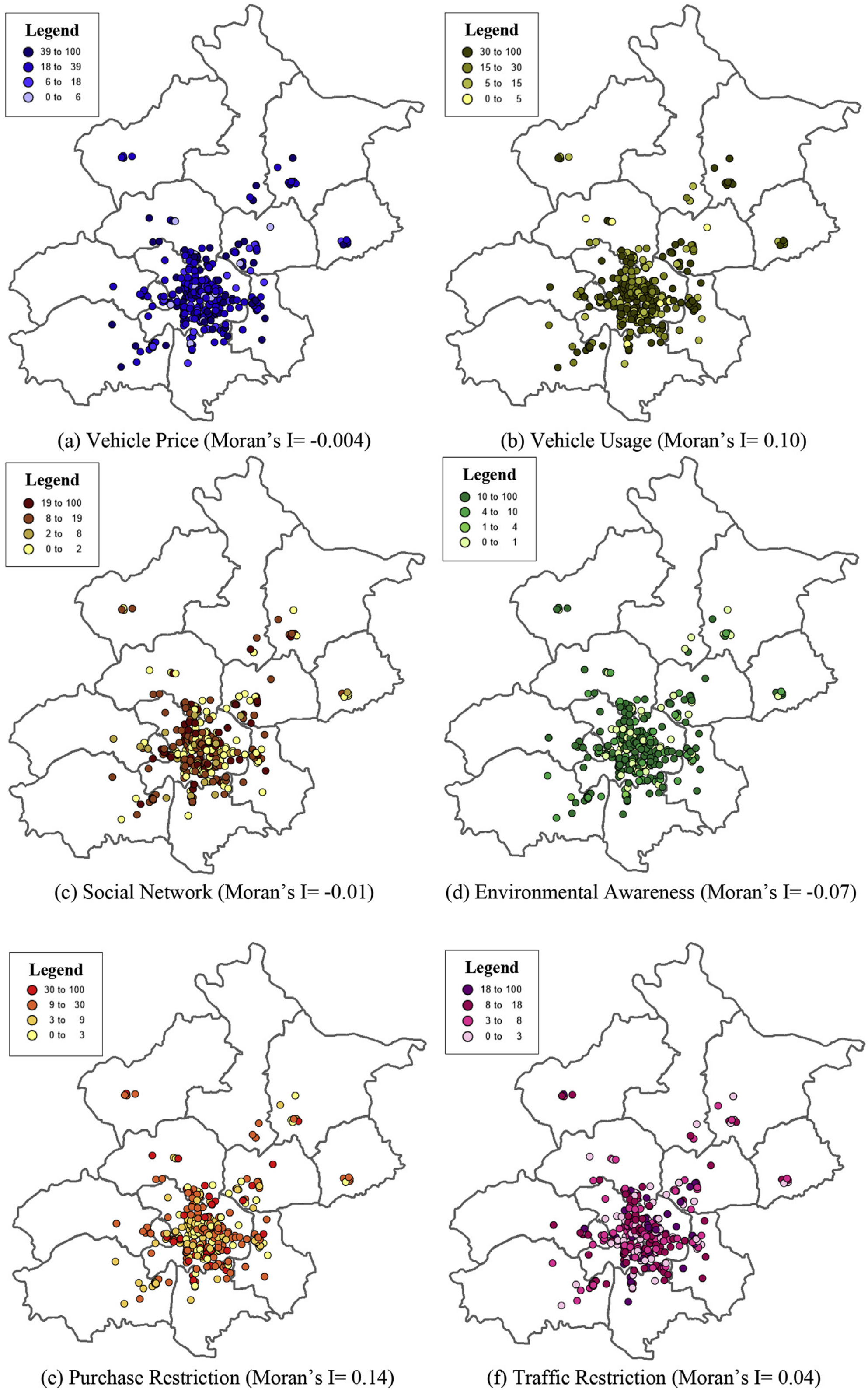


Fig. 4. Spatial distributions of the weights of the six influential factors.

towards vehicle price, vehicle usage, environmental awareness, purchase restriction and traffic restriction were associated with different attributes, apart from the factor of social network. However, the three types of social influence, namely friend, neighbour and global influences, which were collectively referred to as social network here, were separately associated with some socio-demographic attributes. This suggests that the three types of social influence may have to be considered separately, and should not

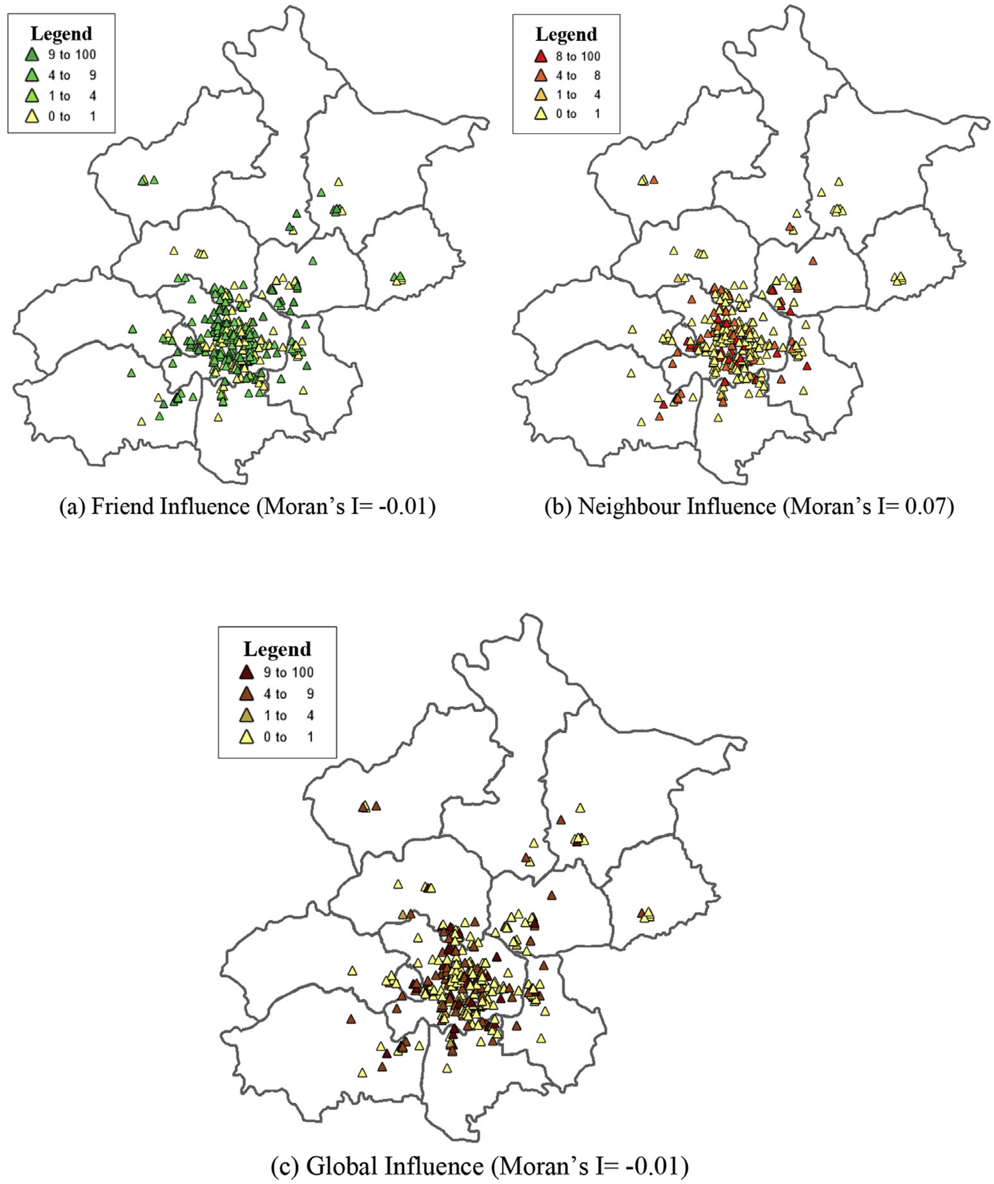


Fig. 5. Spatial distributions of the weights of the three types of social influence.

be studied as a collective term, social influence (or social network). Furthermore, the weights of each factor were analysed from a spatial perspective, using Moran's I which is a measure of global spatial autocorrelation. The results suggest that among the six factors, only vehicle usage (Moran's I = 0.10) and purchase restriction (Moran's I = 0.14) tend to somewhat cluster spatially, suggesting that people with similar attitudes towards vehicle usage and purchase restriction tend to live close to each other, as probably these two factors are only associated with the education level (according to the MNL models) and people with similar education levels tend to live close to each other (note Moran's I for the education level is 0.29).

As discussed above, the research findings can be applied in the modelling of EV purchase behaviour. The future work will be focused on developing an agent-based EV market model incorporating the utility function developed in this paper. In order to take into account both heterogeneity and spatial factors (e.g., neighbour effect), the EV market model needs to be coupled with a population synthesizer (Pritchard and Miller, 2012), a social network generator (Arentze et al., 2012), and an activity-based travel demand model (Horni et al., 2016; Zhuge et al., 2017). Specifically, population synthesizer is used to generate a synthetic population containing individuals and households, as well as their attributes (e.g., income and car ownership) (Pritchard and Miller, 2012; Zhuge et al., 2016a, 2018a), which can be used as the inputs of the MNL models to predict the weights of each factor; the social network generator is used to generate a population-wide social network (Arentze et al., 2012; Zhuge et al., 2018b), so that the three types of social influence can be quantified and the results can be further used as the inputs of the utility function; Activity-based travel demand model, which is used to simulate the daily travel of each individual in the population (Horni et al., 2016), can be used to quantify the vehicle usage and environmental awareness (e.g., the total amount of vehicular emissions) by aggregating the micro-simulation results. In addition, this paper used four general clusters, namely "Very High", "High", "Medium" and "Low", to group the weights of each factor, using a K-means clustering algorithm with K set to 4. These four clusters were further used as alternatives of the MNL models to

relate the weights of each factor to socio-demographic attributes. Although this clustering method is unlikely to heavily influence the application of the estimated MNL models to predict the weight of each factor, more investigation into the clustering method (for example, using a different K) would be helpful for better understanding the relationships and further for predicting the weights.

Acknowledgement

This research was supported by the National Natural Science Foundation of China (Grant No. 51678044) and ERC Starting Grant #678799 for the SILCI project (Social Influence and disruptive Low Carbon Innovation). We would also thank Dr. Mike Bithell for comments on the survey design.

Appendix

Appendix 1. Questionnaire Survey in Beijing

In order to get the weight (or the relative importance) of each factor, the following scenario was given to the participants in the questionnaire survey in Beijing:

Assuming that you are purchasing vehicles (either electric or conventional vehicles), please compare the following factors that may influence your decisions and score them with weights.

An Example: One participant views that the driving experience (Factor 2) is most important, accounting for 45%; the second important factors is vehicle price (Factor 1), accounting for 25%; The constraints on vehicle purchase permit and usage (end-number licence plate) are least influential.

Factor 1 Vehicle Price (The final price, considering any subsidy, etc.)	Factor 2 Driving Experience (On Driving, Parking, Refuelling/Charging, Cost, Safety, etc.)	Factor 3 Social Network (Influence from Friends, Neighbours and Social Media)			Factor 4 Environmental Awareness (EVs are good for Air Quality)	Factor 5 Purchase Permit (Higher Winning Probability of EV Permits)	Factor 6 Usage Constraint (End-number licence plate)
25%	45%	10%			10%	5%	5%
		Friends	Neighbours	Social Media			
		5%	0%	5%			

Note: The total score is 100%.

Factor 1 Vehicle Price	Factor 2 Driving Experience	Factor 3 Social Network			Factor 4 Environmental Awareness	Factor 5 Purchase Permit	Factor 6 Usage Constraint
		Friends	Neighbours	Social Media			

Please now give your weights here:

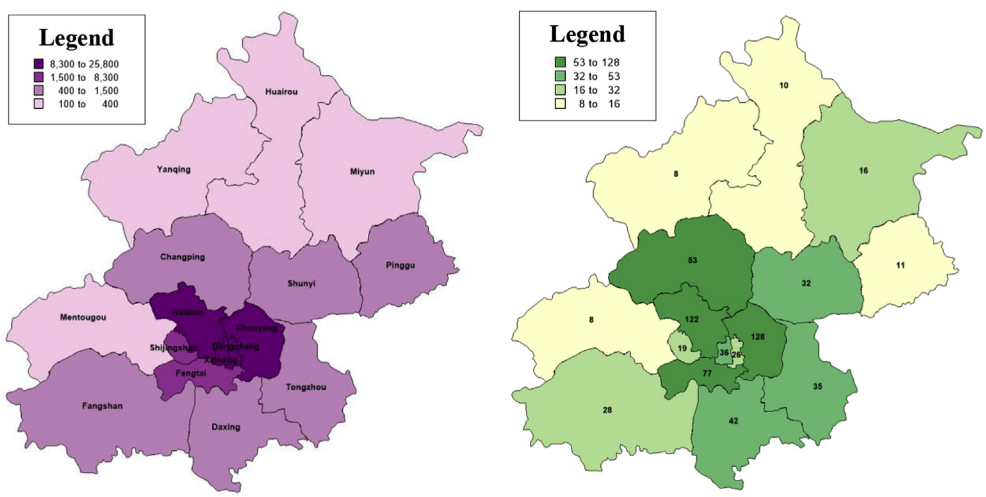
Appendix 2. General Results of the Questionnaire Survey

Table 7 compares the target and actual sample sizes of each region, suggesting that the actual sample sizes are higher. It should be noted that the valid sample sizes for different questions may vary, as some of the respondents did not answer those sensitive questions, such as the residential location. As a result, the valid sample size for the spatial analysis in Section 5.3 is smaller than the total actual sample size (651), for example.

Table 7
Target and Actual Sample Sizes

ID	District Names	Target Sample Size	Actual Sample Size
1	Dongcheng	24	26
2	Xicheng	34	36
3	Chaoyang	100	128
4	Fengtai	59	77
5	Shijingshan	17	19
6	Haidian	93	122
7	Fangshan	26	28
8	Tongzhou	34	35
9	Shunyi	26	32
10	Chanpin	49	53
11	Daxing	39	42
12	Mentougou	8	8
13	Huairou	10	10
14	Pinggu	11	11
15	Miyun	12	16
16	Yanqing	8	8
Total		550	651

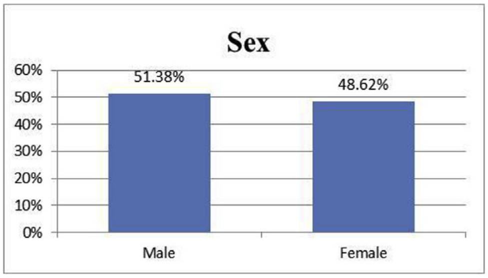
Fig. 6 shows the population density and actual sample sizes. It is worth noting that Fig. 6-(b) maps the sample sizes of each administrative region based on survey locations (where the questionnaire survey was conducted), rather than the residential locations or workplaces of participants.



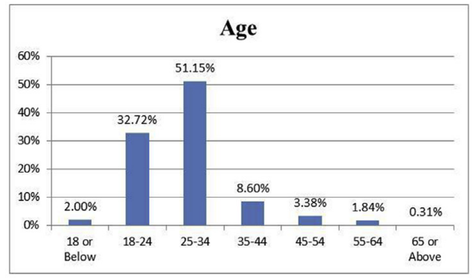
(a) Population Density in 2014

(b) Spatial Distribution of Sample Size by Survey Location

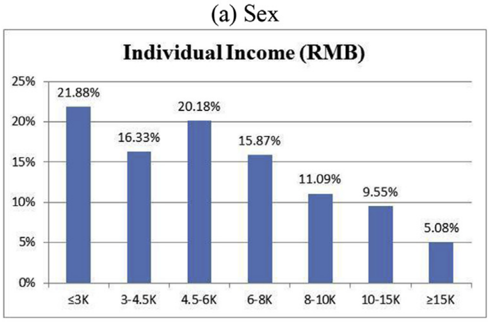
Fig. 6. Maps of Population Density and Actual Sample Sizes.



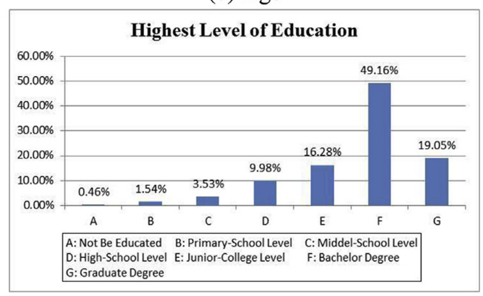
(a) Sex



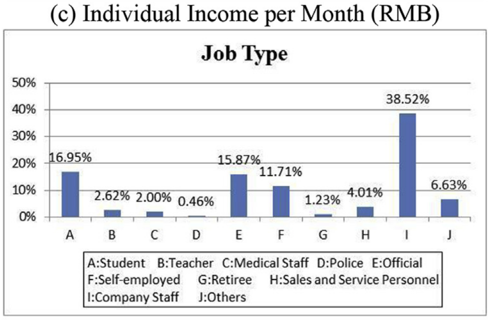
(b) Age



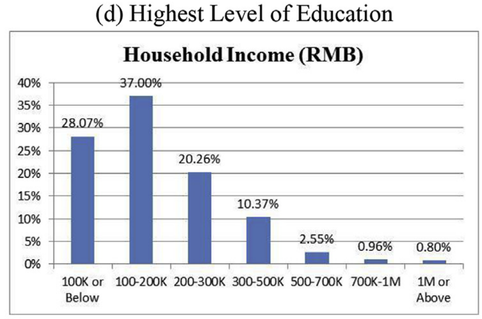
(c) Individual Income per Month (RMB)



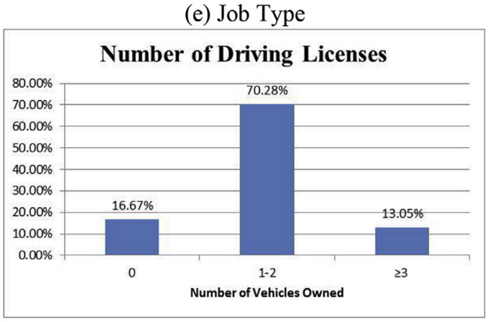
(d) Highest Level of Education



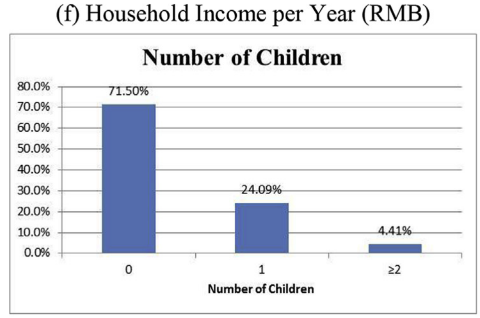
(e) Job Type



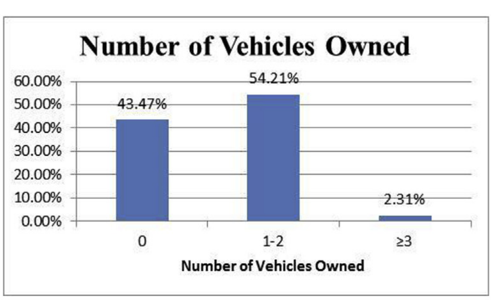
(f) Household Income per Year (RMB)



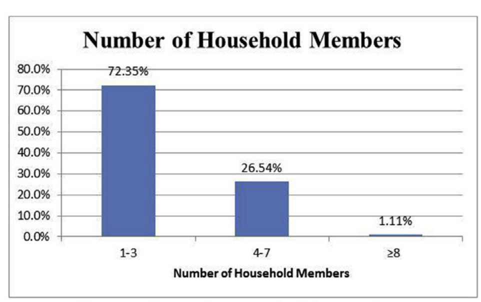
(g) Number of Driving Licenses in a Household



(h) Number of Children in a Household



(i) Number of Vehicles Owned by a Household



(j) Number of Household Members

Fig. 7. Characteristics of Participants and their Households.

Appendix 3. Relationships between the Weight of Influential Factors and Socio-Demographic Attributes

Appendix 3.1Vehicle Price

Fig. 8 shows the relationships between vehicle price and the statistically significant variables, including individual income, number of children and education level. It should be noted that the vertical axis in each subfigure is the percentage of the weight of vehicle price to a specific variable. Taking the number of children (Fig. 8-(b)) for example, to participants with no children, the distribution of their weights of vehicle price is shown by the bar with “0“.

(a) Relationship between Vehicle Price and Individual Income

(b) Relationship between Vehicle Price and Number of Children

(c) Relationship between Vehicle Price and Education Level

Fig. 8. Relationships between Vehicle Price and Significant Variables.

Appendix 3.2Vehicle Usage

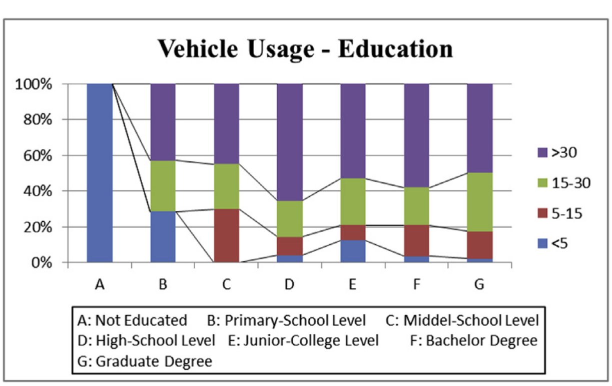
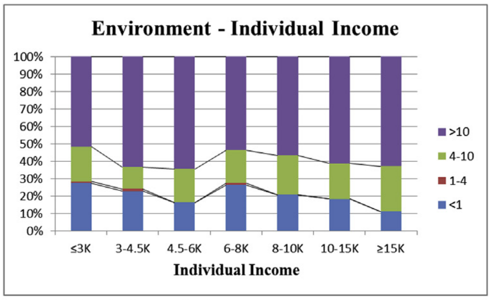
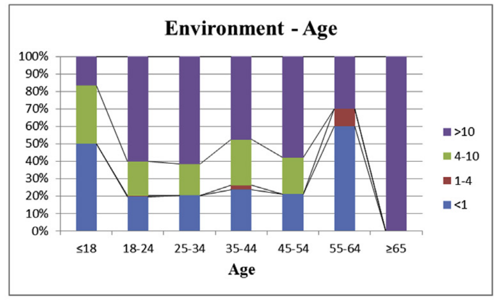


Fig. 9. Relationship between Vehicle Usage and Education Level.

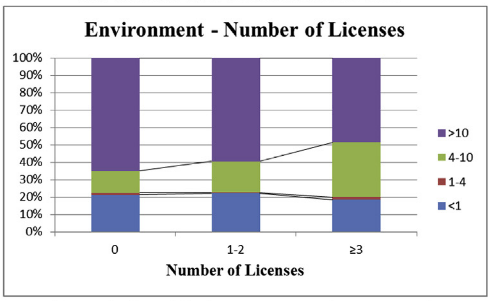
Appendix 3.3Environmental Awareness



(a) Relationship between Environmental Awareness and Individual Income



(b) Relationship between Environmental Awareness and Age



(c) Relationship between Environmental Awareness and Number of Licenses

Fig. 10. Relationships between Environmental Awareness and Significant Variables.

Appendix 3.4Purchase Restriction

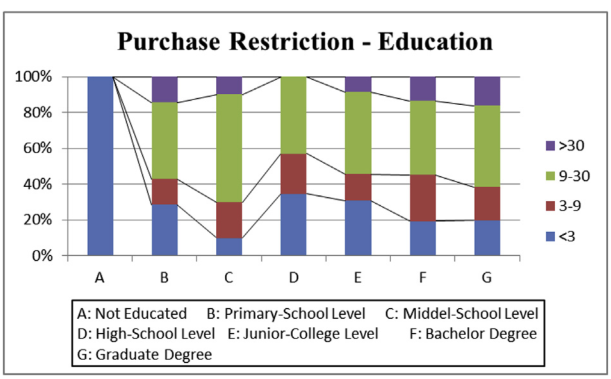


Fig. 11. Relationship between Purchase Restriction and Education Level.

Appendix 3.5Traffic Restriction

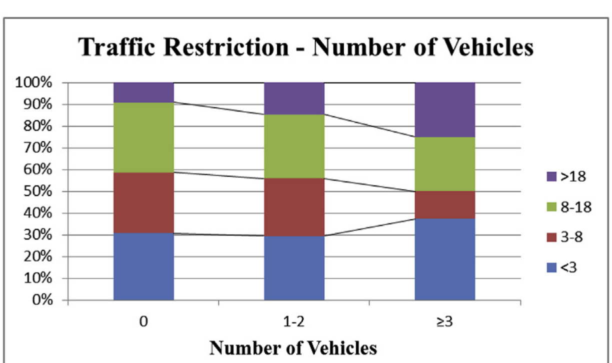


Fig. 12. Relationship between Traffic Restriction and Number of Vehicles.

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